An overview of research on ”passive” brain-computer interfaces for implicit human-computer interaction

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***Abstract*— This paper surveys existing and past research on brain-computer interfaces (BCI) for implicit human-computer interaction. A novel way of using BCI has indeed emerged, which proposes to use BCI in a less explicit way : the so-called “passive” BCI. Implicit BCI or passive BCI refers to BCI in which the user does not try to control his brain activity. Thus the brain activity is assimilated to an input and can be used to adapt the application to the user’s mental state. In this paper, we first study “implicit interaction” in general and recall its main applications. Then, we make a survey of existing and past research on brain-computer interfaces for implicit human-computer interaction. It seems indeed that BCI can be used in many applications in an implicit way, such as for adaptive automation, affective computing, or for video games. In such applications, BCI based on implicit interaction was often reported to improve performance of either the system or the user, or to introduce novel capacities based on mental states.**

***Index Terms*— Brain-computer interface, passive BCI, implicit interaction, EEG**

I. INTRODUCTION

A Brain-Computer Interface (BCI) is a communication system which uses brain activity as an input channel [1]. Different techniques exist to provide brain signals to BCI such as Electroencephalography (EEG), which measures the electrical activity generated by the brain, and functional Near InfraRed Spectroscopy (fNIRS) which measures the changes in the ratio of oxygenated hemoglobin in blood due to neural consummation.

The original goal of BCI is to provide a communication and a control channel for people with severe disabilities, especially people who are completely paralyzed. Most BCI have been used for a direct or “explicit” control, e.g. users trying to control a cursor or to select letters on a computer screen by using their mental activity. The channel transfer rate of these applications remains under 25 bits/minute [1]. Such “explicit” BCI often requires a long training period, but still remains a solution for patients.

BCI can also be used by healthy users who have access to other input devices such as mouse, keyboard, gamepad, etc [2]. Thus, the perspective of BCI usage can change. One solution consists in using the information acquired with the BCI to provide an implicit interaction between man and machine. By implicit interaction we refer to : “an action performed by the user that is not primarily aimed to interact with a computerized system but which such a system understands as input” [3]. This kind of interaction can be done via BCI, which in this case is sometimes called “passive BCI” [4][5][6].

This paper provides an overview of the existing and past research on brain-computer interfaces for implicit human-computer interaction. In the first section, we will study implicit interaction in general. We will review the different definitions that have been given to implicit interaction. Then we will present the classical techniques used for acquiring implicit information. Thereupon we will review classical applications of implicit interaction. In the second section we will see how BCI can be used for implicit interaction. We will study the usage of the term “passive BCI” and present how it can be considered as an implicit interaction based on BCI. Then we will present typical implicit information which can be extracted with a BCI. Last, we will review current applications of BCI for implicit interaction.

II. IMPLICIT INTERACTION

We all know how to interact explicitly or voluntarily with computers : we use this everyday when we select a hypertext link with the mouse for example. Explicit interaction refers to this kind of interaction. But there also exists a way to interact less explicitly with computers such as for human-to-human interaction with non-verbal communication.

In the literature there are different terms or concepts proposed to qualify an interaction which is not voluntarily or explicitly controlled. We list and define all these terms in the following section.

A. Different definitions of implicit interaction

In 1993, Nielsen introduces the term “NonCommand” user interfaces in [7]: “This term may be a somewhat negative way of characterizing a new form of interaction but the unifying concept does seem to be exactly the abandonment of the principle underlying all earlier interaction paradigms: that a dialogue has to be controlled by specific and precise commands issued by the user and processed and replied to by the computer. These new interfaces are often not even dialogues in the traditional meaning of the word, even though they obviously can be analyzed as having some dialogue content at some level since they do involve the exchange of information between a user and a computer.”

Jacob et al. reuse this term and refine it as : “passive equipment that senses the user” and uses “less intentional actuation of a device or issuance of a command, but are more like passive monitoring of the user” [8].

Another view is provided by Schmidt in [3], who uses the expression *implicit human-computer interaction* : “an action performed by the user that is not primarily aimed to interact with a computerised system but which such a system understands as input”.

Zander et al. [6] also use the term implicit interaction : “implicit interaction can be defined as an unconscious action that is integrated in another action, for example mimic and gesture”.

All these terms : “NonCommand” user interface, “implicit human-computer-interaction”, “implicit interaction”, seem closely related. They seem to refer to the same idea : an interaction process that is not based on direct, explicit, or voluntary action of the user, but more on the state of the user in a particular context. Both the user’s state and the given context can thus be associated with the expression *implicit information*.

B. Techniques for acquiring implicit information

Implicit information can be acquired with different techniques. Allanson and Fairclough provide a description of numerous physiological techniques which could be used for implicit interaction [9]. We can stress Galvanic Skin Response (GSR) which provides information about the emotional and cognitive states of the user.

Specific devices such as gaze-tracking systems can also access information implicitly generated by the user [10]. Indeed, duration of gaze on displayed elements provides information about the cognitive processes that are used.

In the following section we present classical applications using some of these inputs. Brain activity can also provide implicit information depicted in section III.

C. Classical applications of implicit interaction

Classical applications of implicit interaction can be categorized in four categories : *1)* adaptive automation, *2)* applications that adapt content according to user’s implicit interest, *3)* applications related to affective computing and *4)* virtual reality and video games.

1) Implicit information to adapt the level of automation. First, we can consider the field of adaptive automation. Adaptive Automation (AA) refers to automation system in which the task is allocated dynamically between user and machine. The allocation of this task can be based on user’s implicit information (e.g operator state) [9]. In [11] the user’s arousal is constantly measured by a Galvanic Skin Response (GSR) monitoring system. The interaction here is based on the level of arousal which, under a threshold can launch an action. If the arousal is low for a long time an alarm sound signal is played and the user must increase concentration.

2) Applications that adapt content according to user implicit interest. A second kind of application which can use implicit information corresponds to applications that adapt the content according to user’s implicit interest. Hyrskykaria presented in [10] the “iDict” application which is a gaze-aware help for readers. It displays translation of foreign words that are not understood by the user. To detect which word needs to be translated, it uses the fixation duration on words. Another similar application is the one proposed by Jacob in [12]. The screen is divided into two windows, the first showing a map of an ocean with icons for ships, the second displaying information about ships. Information is displayed only when the user looks at a specific ship. It does not matter here if the look is intentional or not.

Another way to take care of user’s implicit interest is presented by Starker et al. in [13]. They proposed an interactive story teller that uses a gaze system to choose which part of the story to develop in relation to what the user is glancing at. The user, never explicitly tells the computer about what to say.

3) Affective computing. A third kind of application which can use implicit interaction concerns applications related to affective computing. Affective computing is a new field of research in computer science introduced by Picard [14]. The goal of affective computing is to allow computers to recognize human emotions, to respond to them and also to express affect. Affective computing is directly related to implicit interaction as implicit information, here the user’s emotional state, is used to interact with the computer [14].

4) Implicit interaction for virtual reality and video games. Finally, we can quote applications concerning the field of virtual reality and video games. Rani et al. presented in [15] a modified Pong game which uses physiological sensors, to adapt the difficulty of a game to the user’s state. Gilleade et al. presented a similar game in which heart rate was used to change the nature of the challenge [16]. For instance the number of enemies was increased if the heart-beat rate decreased. Players reported that the game provided an enjoyable gaming experience. Gilleade et al. also noted that experienced players responded less physiologically as compared with inexperienced gamers [16].

We can also quote the work of Bersark et al. in [17] who use the galvanic skin response to measure the relax state of an user in the game “Relax-to-Win”. In this two-player game, each player controls “by relaxation” the speed of a 3D dragon in a race. The more relax the player is, the faster his dragon will move. Interestingly the user can try to control his stress level to go faster. Thus, the interaction uses implicit information “voluntarily” controlled by the user. In other words, the interaction is here becoming progressively more explicit.

D. Discussion

Implicit information can be acquired with different techniques, notably physiological sensors. Numerous fields of research are concerned with this acquisition and usage of implicit information. It is sometimes difficult to set the limit between implicit and explicit interaction. For example, if the user starts to control implicit information, the interaction becomes then more and more explicit. Some applications like the game "Relax-to-Win" leads to this kind of behavior. Besides, in human-to-human interaction we can observe the same behaviour. For instance, someone can control his voice intonation to appear less stressed (the voice intonation is here considered as the implicit information). We will see that the same behaviour can also occur with implicit interaction based on BCI in the following section.

III. IMPLICIT INTERACTION BASED ON BCI

A. Passive BCI and implicit interaction

The term "passive BCI" has already been used to describe a way to use BCI as an implicit communication channel between user and computer.

Cutrell and Tan were the first to introduce the expression "passive BCI". In [4] they wrote "We think there is a potential to use brain sensing in a more passive context, looking beyond direct system control to make BCI useful to the general population in a wide range of scenarios".

Girouard [5] referred to the work of Cutrell and Tan and defines the term "passive BCI" as : "passive BCIs are interfaces that use brain measurements as an additional input, in addition to standard devices such as keyboards and mice". By developing "passive BCI", her aim is to use brain activity information to create "applications that pay attention to the user" by adapting them to user's mental state.

Another point of view is presented in [6] by Zander et al. who defined "passive BCI" as BCI based not on intended actions of the user, but instead on "reactive states of the user's cognition automatically induced while interacting in the surrounding system".

Passive BCI could thus be considered as a way to interact implicitly with computer based on brain activity. Indeed, BCI used in a passive context, can provide *implicit information*. This implicit information is close to the one provided by other physiological techniques (e.g GSR). In this view, the term *implicit brain-computer interface* could be relevant to describe this kind of use of brain computer interfaces and the so-called "passive BCI". The term *implicit brain-computer interface* highlights the link between implicit interaction in general and interaction based on brain activity.

In the remainder of this paper we will refer to "implicit BCI" and "explicit BCI" defined as follows :

- Explicit BCI : use of BCI in which the user deliberately tries to control his brain activity.
- Implicit BCI : use of BCI in which the user does not try to control his brain activity, which is decorrelated from his primary task.

B. Mental states providing implicit information for BCI

In Table I we provide an overview of typical implicit information and corresponding brain signals, that can be found in the BCI literature up to now.

Implicit information	Brain signal	Ref.
Task engagement	Ratio of rhythms beta/(alpha+theta), beta/alpha, 1/alpha	[18]
Mood, emotion	Frontal EEG asymmetry, Event Related Potential and Evoked Potentials	[19]
Error recognition	Error related potential	[20]
Relaxed alertness	Alpha rhythms	[21]
Mental workload	Blood oxygenation in cortical region (fNIRS)	[22]

TABLE I

TYPICAL IMPLICIT INFORMATION AND CORRESPONDING BRAIN SIGNALS DENOTED IN THE LITERATURE

This table shows that the current measure of brain activity already allows to access various type of implicit information about the user's state, such as mental workload or task engagement. Implicit information related to error recognition can also be acquired. Indeed, an Error-related potential (Errp) occurs following a perceived error made by the subject himself or the interface [20].

We present in the following section the current BCI applications which make use of such signals.

C. Current applications of BCI for implicit interaction

In this section our aim is to present existing applications that use implicit information acquired by brain activity measurement. These systems can be categorized in four categories : *1)* adaptive automation, *2)* implicit multimedia content tagging, *3)* video games, and *4)* error correction as displayed in Table II.

1) Adaptive automation. In the field of adaptive automation, the first brain-based system was developed by Pope et al. [18]. In this system, the allocation between human and machine of a tracking task is done based on an engagement index. This engagement index is calculated using user's brain activity. More recently, Kohlmorgen et al. presented an usage of implicit brain-computer interface in the context of a real driving environment [23]. The user is engaged in a task mimicking interaction with the vehicle's electronic warning and information system. This task is interrupted when high mental workload is detected. This experiment showed better reaction times on average using BCI based on implicit interaction.

2) Implicit multimedia content tagging. Implicit interaction has also been used for tagging multimedia content [24][25][31]. Shenoy and Tan [24] used EEG activity to classify images. They used Event Related Potentials (ERP) that occur in EEG activity after image presentation. Their system was able to classify images matching to human faces vs. inanimate objects with a 75.3% accuracy. For a three-class classification (human faces, vs. animals, vs. inanimate objects) an average accuracy of 55.3% was obtained. Kappoor et al. used these results [25] and proposed to combine BCI with a more classical recognition system. The experiment yielded significant gains in accuracy for the task of object categorization.

In the two aforementioned works users were not aware of the classification task. They were assigned "a distractor

Application	Task	Brain features	Goal	Usage of implicit interaction	Ref
Adaptive automation	Tracking task	Band power ratios	Enhance mental engagement	Adapt automation of the task	[18]
	Driving and distractors	Band power	Maintain low reaction time	Disable a task when high workload	[23]
Multimedia content tagging	Image looking task	ERP	Use brain capabilities for classification task	Analyse brain activity after image presentation	[24]
	Image looking task	ERP	Use brain capabilities to improve automatic classification	Analyse brain activity after image presentation	[25]
Video games	Game (Bacteria Hunt)	Alpha band power	Challenge player to relax	Affect controllability of avatar	[26]
	Game (AlphaWow)	Alpha band power	Enhance immersion	Shift avatar's form	[27]
	Game (Tetris)	Blood oxygenation (fNIRS)	Enhance immersion	Adapt music to the predicted user's task	[22]
	Game (RLR)	Errp	Detect user's feeling of losing control	Detect if the user perceived a system's error	[6]
Error correction	BCI motor imagery task	Errp	Improve explicit BCI	Filter out erroneous system's responses	[28]
	BCI P300 speller	Errp	Improve explicit BCI	Correct errors made by P300 speller	[29]
	Visual discrimination task	Errp	Improve user performance	Correct user's perceived errors	[30]

TABLE II
EXISTING SYSTEMS USING BCI FOR IMPLICIT INTERACTION

task" to force them to look at the display. No feedback about the classification task was provided. This reinforces here the *implicit* property of the *interaction*.

Video content tagging has also been explored [31]. Koelstra et al. proposed to use EEG brain activity to implicitly validate video tag. They demonstrated that incongruent tags could be successfully distinguished by EEG analysis.

3) Video games. Implicit BCI are also used in video games. Different games that use implicit interaction have been developed up to now. Some of them use implicit information to adapt the way the system responds to commands. It is the case of the game "Bacteria Hunt" in which the controllability of the player's avatar is impaired by considering the level of alpha power (which is correlated here to relaxed wakefulness [26]).

Some other games adapt the avatar's characteristics based on implicit information. In "AlphaWoW" [27], which is based on the famous game World of Warcraft, the user's avatar can transform into an animal based on the user's alpha activity.

Another way to use implicit information for games consists in adapting the game environment (e.g background music). Girouard presented in [22] an experiment in which the user is engaged in two successive tasks watching a video and playing a Tetris game. The application was able to predict in which task the user is engaged in, based on measurement of the brain activity. This allowed to adapt the background music accordingly to the task. This adaptation was found to lead to a positive impact on user's satisfaction [22].

Last, some video games can use implicit information to check if the user has perceived a specific game information. In the game developed by Zander et al. [6], the user has to rotate a letter correctly, as fast as possible. Errors are introduced by the system. An implicit BCI is used to detect if the user's mental state reveals that the user has perceived the errors. In this case the speed of rotation is increased. A false positive (a perceived error when there is none) slows the rotation down [6].

We can notice that these games combine the use of classical devices (e.g keyboard) with an implicit BCI. One of them also uses an explicit BCI together with an implicit BCI [26].

4) Error detection and correction. Last, we can quote systems that are not related to a specific field of applications but which use detection of error potentials. In [30], Parra et al. use the detection of error potentials in brain activity to correct errors in a visual discrimination task. In this study the users had to push buttons corresponding to visual stimuli. The user sometimes failed and perceived error shortly after the action. The system could then identify error mental state and correct user's actions.

The use of error potential was also proposed to correct errors in explicit BCI systems [20]. Ferrez and Millàn used error potential detection to filter out erroneous responses of a BCI based on motor imagery [28]. Dal Seno et al. also addressed the automatic detection and correction of the errors made by a P300 speller [29].

D. Discussion

As shown in Table II, implicit interaction with BCI can have different goals : improving user's performance, improving system's performance, using brain capabilities, or enhancing player's gaming experience. This overview also shows that applications can combine the usage of both implicit and explicit BCI simultaneously. This combination can lead to the improvement of explicit BCI [28][29]. Ferrez and Millàn found indeed a bit rate three times higher when using implicit BCI in combination with explicit BCI [28]. The two types of interaction (explicit and implicit) can also be used in parallel without link between them. In this case, there might be a risk of overlapping between implicit and explicit signals. Indeed, Mühl et al. observed that Steady State Visually Evoked Potential (SSVEP) stimulation could interfere with alpha power (thus explicit BCI might influence implicit BCI here) [26].

As for general implicit interaction based on other signals than brain activity, the frontier between explicit and implicit is sometimes difficult to establish. The user can indeed try to use the implicit communication channel in an explicit way (i.e. the user tries to explicitly modify implicit information). This kind of behaviour should also be taken into account. In contrast, some applications seem completely implicit, since the user is not aware of the implicit information process [24][25], and does not get any associated feedback during the task.

IV. CONCLUSION

In this paper we surveyed existing and past research on brain-computer interfaces for implicit interaction. Implicit interaction is an interaction process which is not based on direct, explicit and voluntary user's action, but more on user's state in a particular context. Classical applications of implicit interaction include adaptive automation, applications that adapt the content to user's implicit interest, affective computing, or video games.

Implicit interaction can be based on a brain-computer interface, which is then sometimes called a "passive BCI". Implicit or passive BCI turned out to be able to improve performance of both user and system. For instance, explicit BCI can be improved when combined with an implicit one such as when correcting P300 Speller's output using mental error detection. Implicit BCI can also help enhancing user's experience when interacting with computers such as in video games in which user's avatar can be transformed according to user's mental state.

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